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Classifying High-noise EEG in Complex Environments for Brain-computer Interaction Technologies

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14. ABSTRACT

Future technologies such as Brain-Computer Interaction Technologies (BCIT) or affective Brain Computer Interfaces (aBCI) will need to function in an environment with higher noise and complexity than seen in traditional laboratory settings, and while individuals perform concurrent tasks. In this paper, we describe preliminary results from an experiment in a complex virtual environment. For analysis, we classify between a subject hearing and reacting to an audio stimulus that is addressed to them, and the same subject hearing an irrelevant audio stimulus. We performed two offline classifications, one using BCILab (*1*), the other using LibSVM (*2*). Distinct classifiers were trained for each individual in order to improve individual classifier performance (*3*). The highest classification performance results were obtained using individual frequency bands as features and classifying with an SVM classifier with an RBF kernel, resulting in mean classification performance of 0.67, with individual classifier results ranging from 0.60 to 0.79.

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Abstract. Future technologies such as Brain-Computer Interaction Technologies (BCIT) or affective Brain Computer Interfaces (aBCI) will need to function in an environment with higher noise and complexity than seen in traditional laboratory settings, and while individuals perform concurrent tasks. In this paper, we describe preliminary results from an experiment in a complex virtual environment. For analysis, we classify between a subject hearing and reacting to an audio stimulus that is addressed to them, and the same subject hearing an irrelevant audio stimulus. We performed two offline classifications, one using BCILab [1], the other using LibSVM [2]. Distinct classifiers were trained for each individual in order to improve individual classifier performance [3]. The highest classification performance results were obtained using individual frequency bands as features and classifying with an SVM classifier with an RBF kernel, resulting in mean classification performance of 0.67, with individual classifier results ranging from 0.60 to 0.79.

Keywords: EEG, affect, self-relevant, classification, noise.

1 Introduction

Brain-Computer Interaction Technologies (BCIT) aim to use electroencephalography (EEG) and other physiological measures to enhance a healthy user's performance with a system [4]. These technologies, and similar technologies such as affective brain-computer interfaces (aBCI), have promising applications such as monitoring fatigue or recognizing extreme negative affect (i.e. stress or anger). These applications could provide important and relevant information about the performance of a Soldier in real time, ideally allowing the identification and mitigation of performance degradation before tragic mistakes occur. However, for these technologies to achieve their full potential, they will need to function in an environment with higher noise and complexity than currently seen in traditional laboratory settings. Further, many traditional experiments use a reductionist approach of studying a single task performed in isolation. For these systems to be viable, they

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must detect relevant user states or emotions when an individual is performing multiple concurrent tasks.

In this paper, we begin to address these noise and complexity challenges by describing preliminary results derived from an experiment in a complex virtual environment. In this experiment, teams of two Soldiers performed Vehicle Commander (VC) and Driver roles in a simulated Stryker vehicle on a six degrees-of-freedom (DOF) ride motion platform. The focus of the EEG and behavioral data collection was on the VC, who interacted with the Driver and performed multiple overlapping tasks, such as route planning, maintaining local situational awareness, and monitoring and responding to radio communications. Additionally, the EEG data collected from the VC in this experiment has large amounts of noise artifacts, including those caused by reaching and speaking, unconstrained eye and head movements, and the movements of the motion platform. EEG collected in this environment will provide a test bed for evaluating data processing methods for real-world applications.

For this preliminary analysis, we are attempting to classify between a Soldier hearing and reacting to a self-relevant audio stimulus, and the same Soldier hearing a irrelevant audio stimulus. Reliably accomplishing this task would demonstrate a capability for extracting physiological information in a complex environment, and potentially provide the capability for performing minor optimizations of a vehicle crew station interface. The complexity of the environment will likely result in high classification error percentages, leading us to perform an individual-based analysis. However, by performing this analysis we obtain a baseline performance metric that demonstrates the potential for analyzing this complex data set. In addition, by performing classifier training on individuals we hope to improve classifier performance for particular individuals, instead of using classifiers trained across groups or on normative data [3].

This paper is organized as follows: section 2 will discuss work relevant to the goals of this paper. Section 3 will describe the experimental methodology. Sections 4 and 5 will describe the analysis methods and discuss the results, and the paper concludes in section 6.

2 Related Work

In this preliminary analysis, we aim to classify the neural processing related to self-relevant auditory communications compared to irrelevant auditory communications. The self-relevance of an event has considerable effects on its ability to catch our attention, and to the emotional value assigned to that event [5], [6]. Prior research indicates that self-relevant communication has particular underlying neural and physiological codings that classification can be based on. While much of the research demonstrating neural correlates of self-relevance has focused on fMRI studies [7], there is some research showing the relationship between self-referential stimuli and electrophysiological correlates. For example, Gray et al. [8] have shown that self-relevant visual stimuli have a significant effect on event-related P300 latency and amplitude, and Tanaka et al. [9] report a focal response (N250) in right posterior channels when viewing pictures of oneself. In addition to these studies of self-relevant

Fig. 1. Vehicle Commander (VC) Warfighter-Machine Interface (WMI), consisting of a 180º field-of-view banner across the top, a 60º field-of-view window on the left hand side, and an overhead map on the right hand side.

visual stimuli, several researchers have shown neural correlates of auditory recognition using both fMRI and EEG, while Krause et al. [10] showed a statistically signification relationship between an auditory recognition task and event-related desynchronizations in the upper (10-12 Hz) and lower (8-10 Hz) alpha frequency bands of the EEG signal. In short, these studies collectively suggest a differentiation in the neural processing of self-referential stimuli, whether visual or auditory, and it is this differentiation in the brain signal that our classification approach seeks to identify despite the noise in the recorded EEG signal and the complexity of the task environment.

3 Experimental Methodology

3.1 Subjects

The subjects were 14 U.S. Army Sergeants, all male, ranging from age 27 to age 50, with mean age 34.5 from Military Occupational Specialty (MOS) 11B (Infantryman), MOS 19D (Cavalry Scout), and MOS 19K (Armor Crewman). The Soldiers were all combat veterans of Iraq or Afghanistan, and all from the U.S. Army Maneuver Center of Excellence at Fort Knox, KY and Fort Benning, GA. Two of the subjects were excluded from the analysis due to technical difficulties during the data collection, and two subjects were excluded due to failure to accomplish experimental tasks, resulting in 10 subjects being utilized for the analysis.

3.2 Design and Procedure

The goal of the experiment was to study commander task performance under varying task load conditions during team operations in a complex Army-relevant virtual

environment. During the experiment, teams of two Soldiers performed six simulated missions consisting of traveling in a Stryker vehicle from a Forward Operating Base (FOB) to a nearby small desert metropolitan area, visiting three sequential checkpoints in the city area, and then returning to the FOB. One Soldier was assigned the role of the Vehicle Commander (VC), while the other Soldier was assigned to be the Driver. Each Soldier would spend one day as VC, and one day as the Driver. The simulated Stryker was equipped with a Closed-Hatch Local Situational Awareness (LSA) system, consisting of six external cameras covering a 360º area around the vehicle that were accessible from the VC crew station (Fig. 1).

During each mission, the VC performed numerous tasks that can be categorized into three main task groupings:

1. Overseeing mission progress and ensuring that the vehicle arrived at each checkpoint within a specific time range. This included supervising the Driver and providing turn-by-turn directions through the city, halt/resume commands, and immediate command driving around difficult obstacles in the environment.
2. Maintaining visual LSA, which included detecting road obstacles and traffic conditions relevant to navigating the environment, and reporting the position of uniformed local forces and objects identified as threats over the radio network to a simulated Tactical Operating Commander (TOC).
3. Maintaining auditory LSA, which included monitoring and responding to radio communications about mission status from the TOC and verbally interacting with the Driver.

In order to explore differential effects of task loading, the portion of the mission consisting of the ride from the FOB into the metro area was designed to induce much lower cognitive load than the portion of the mission taking part inside the metro area. There were considerably more audio and visual stimuli, and more pedestrian and vehicle traffic within the metro area than there were outside of it.

3.3 Auditory Stimuli

While there are many potential aspects of this data set that could be mined for results, including neural or physiological correlates of visual targets or error-related signals induced by driver mistakes such as vehicle-vehicle or vehicle-pedestrian contact, the focus of this preliminary analysis is on the auditory stimuli. The VC monitored four audio channels during the course of the experiment: primary audio stimuli, background audio stimuli, all-listener audio stimuli, and Driver communications.

Primary audio stimuli consisted of pre-recorded messages from a single radio operator (a simulated TOC) that were directed to the VC's call sign, "Blue 4." The primary audio stimuli were directly associated with the mission being performed, and were triggered either by trip lines in the virtual environment or when specific scenario conditions were met. For the purposes of this analysis we have divided the primary audio stimuli into three categories (Table 1): (1) messages that tell the VC to change between radio communication nets, which the VC would perform by pressing a button on the crew station; (2) messages that ask a question of the VC, which the VC would respond to by pressing a push-to-talk button and speaking; and (3) messages that require minimal response from the VC (i.e. the VC would respond by pressing the push-to-talk button and saying "roger").

Table 1. Audio Stimuli Categorizations

Category Label	Stimulus Type	Total Quantity
A1	Primary: Change between radio nets	625
A2	Primary: Asking question of Soldier	321
A3	Primary: Other primary communication	1563
B1	Background: Messages to Blue 12	634
B2	Background: Other background communications	501
C1	All Listeners: Change radio net status	93
C2	All Listeners: other communications	293

Background audio stimuli consisted of pre-recorded messages from various other speakers which were not directed to the VC, were not mission-relevant, and were randomly triggered. We have divided the background audio stimuli into two categories: (1) messages to the call sign 'Blue 12', which is similar to the VC's call sign; and (2) other background communication.

All-listener audio stimuli consisted of pre-recorded messages that were directed to all listeners on the channel, were not mission-relevant, and were randomly triggered. We have divided these stimuli into two categories: (1) messages that tell all of the listeners (including the VC) to change the radio net status, which the VC would perform by pressing a button on the crew station; and (2) messages that provide information to all listeners (including the VC).

Relevant and irrelevant audio stimuli were clearly defined through the use of call signs. All Army radio messages are prefaced with the call sign of the Soldier to whom they are directed. Thus, within the first 0.5 to 1.0 seconds of the radio message, the VC was able to determine the relevancy of the audio stimulus. The Soldiers successfully responded to almost all relevant primary audio stimuli (i.e., all communications that began with "Blue 4" followed by the question or directive from the Tactical Operating Commander), which indicates successful identification and comprehension of the VC-directed auditory communications. The driver communications were less controlled since the Driver was a live participant rather than a recorded voice like the Tactical Operating Commander. For this preliminary analysis, the VC communication with the Driver was ignored.

3.4 Experimental Setup

EEG was collected from the VC using a 64-channel BioSemi active-electrode EEG system placed according the 10-20 international system, referenced to averaged mastoids, and recorded at 256 Hz. In addition, horizontal EOG was collected from two electrodes placed on the outer canti of the eyes and vertical EOG was collected from two electrodes placed above and below the right eye.

The Driver viewed the simulated environment through a 60º straight-ahead field of view, and interacted with it through a yoke, and two pedals (gas and brake). The VC interacted with the simulated environment through a crew station with 2 touchscreens, through which he had access to the full 360º LSA system, a digital map of the area, and the ability to perform any mission-relevant tasks (Fig 1). The VC also had a paper map for planning the mission route.

The VC performed the experiment while riding on the 6-DOF servo-hydraulic Ride Motion Simulator (RMS) platform at the U.S. Army Tank and Automotive Research, Development, and Engineering Center (TARDEC). The RMS platform was developed at TARDEC for simulating the ride of military vehicles, and it provides motion cues to the occupant derived from physics-based dynamics models of the vehicle and its interaction with the terrain.

The simulated environment consisted of a FOB near a small desert metropolitan area. Within the metro area, there were six checkpoints. Three checkpoints were used in each of the six missions performed by the subjects. Pedestrian and vehicle traffic also served as distracters and obstacles. Behavioral data was collected from the simulated environment, including but not limited to: all of the VC's crew station interactions, timing and audio of all communications, what camera the VC used at any given time, and the position and heading of the simulated Stryker in the environment.

4 Feature Extraction and Classification

For this preliminary analysis we performed two separate sets of offline classifications between a Soldier hearing and reacting to a self-relevant audio stimulus, and between the same Soldier hearing an irrelevant audio stimulus. The first classification set was performed using BCILab [1], an open-source tool for BCI development in MATLAB (Mathworks; Natick, MA) developed at the Swartz Center for Computational Neuroscience at the University of California, San Diego. The second set of classifications was performed using the support vector machine (SVM) library LibSVM [2], developed at National Taiwan University, Taipei, Taiwan. Distinct classifiers were trained for each individual Soldier taking part in the experiment. It has been our experience that, on data such as this, individually-trained classifiers tend to outperform classifiers trained on group or normative data [3].

4.1 BCILab Procedure

The BCILab analysis was performed using BCILab's built-in epoching, filtering, feature extraction, and classification capabilities to analyze the data. The data was downsampled to 100 Hz, bandpass filtered to 1-50 Hz, and epoched from 0.5 seconds to 4.5 seconds after the audio stimulus, with baseline removal performed for each epoch. This epoch size provided the best performance of those tried. Feature extraction was performed using BCILab's log bandpower paradigm, which uses the log variance of the spectral power over the entire 1-50 Hz frequency for each channel for each epoch as the features passed to the classifier, which in this case was a linear discriminant analysis (LDA) classifier. Classifiers were trained and tested for each individual using 10-fold classification validation.

4.2 LibSVM Procedure

For the LibSVM analysis, the data was bandpass filtered to 1-50 Hz, and epoched from 0.5 seconds to 4.5 seconds after the audio stimulus, after which the epochs were detrended. Feature extraction consisted of the bandpower of multiple frequency bands for each channel at each epoch. The frequency bands used were those defined

by Andreassi [11], consisting of the delta (1-3 Hz), theta (4-7 Hz), alpha (8-13 Hz), low beta (14-20 Hz), high beta (21-30 Hz), and the gamma (31-50) bands. The features were scaled on a 0 to 1 range, and classified using an SVM with a radial basis function (RBF) kernel and 10-fold validation. SVM parameters were defined by manual search through the space of possibilities.

Table 2. Mean classifier performance across all subjects

Condition	BCILAB	LibSVM	Actual
A (all) vs. B (all) + C(all)	0.54±0.038	0.60±0.038	0.60 / 0.40
A (all) vs. B (all)	0.57±0.044	0.62±0.048	0.67 / 0.33
A (all) & C (all) vs. B (all)	0.57±0.033	0.67±0.048	0.70 / 0.30
A1 & A2 & C1 vs. B (all)	0.64±0.066	0.65±0.054	0.47 / 0.52
A1 & A2 vs. B (all)	0.66±0.073	0.67±0.053	0.45 / 0.55

4.3 Results

Classifications were performed based on the previously-defined categories of audio stimuli, shown in Table 1. The performance value provided is the mean of the true positive and true negative result percentages across the 10-fold results of the classifiers trained for all subjects. We performed five primary classifications (Table 2): stimuli directly addressed to the VC vs. stimuli that were not (shown in row 1), stimuli directly addressed to the VC vs. irrelevant audio stimuli addressed neither to the VC nor to all listeners of the channel (row 2), stimuli directly or indirectly addressed to the VC vs. irrelevant audio stimuli (row 3), stimuli that required a major response (i.e. crew station interaction or complex verbal response) vs. irrelevant audio stimuli (row 4), and stimuli directly addressed to the VC that required a major response vs. irrelevant audio stimuli (row 5). To show individual classifier performance, the 10-fold performance values for each individual subject for the primary audio that required a major response vs. irrelevant audio stimuli condition are shown in Table 3.

Table 3. 10-fold individual classifier performance for the A1 & A2 vs. B (all) condition

Subject	BCILab	LibSVM	Actual A1 & A2
1	0.78	0.79	0.46
2	0.66	0.64	0.47
3	0.59	0.67	0.49
4	0.61	0.60	0.51
5	0.66	0.62	0.46
6	0.60	0.65	0.47
7	0.69	0.67	0.42
8	0.78	0.72	0.4
9	0.61	0.66	0.48
10	0.61	0.67	0.45

5 Discussion

The highest classification performance results were obtained by classifying the recognition of relevant audio with a major response to irrelevant audio, with both BCILab and LibSVM providing similar results in the 0.65-0.67 range. However, one potential concern regarding the results arises from the fact that during each scenario there were high-activity time periods (those within the urban area, which had increased tasks and distracters) and low-activity time periods (those outside the urban area). In order to ensure that the results were not showing a distinction between high activity and low activity, we ran two additional sub-classifications, one comparing relevant audio with a response vs. irrelevant audio in low-activity time periods, and another comparing the audio stimuli that occurred in high-activity time periods. The results were comparable to the overall classification (Table 5), indicating that we are classifying based on the audio stimuli conditions, not on the low vs. high-activity condition.

Table 4. Mean classifier performance across all subjects for the A1 & A2 vs. B2 & B4 condition with low-activity and high-activity conditions

Condition	BCILab	LibSVM	Actual
Low-Activity	0.64±0.077	0.64±.097	0.47 / 0.53
High-Activity	0.64±0.046	0.62±.081	0.45 / 0.55

Another potential concern with the analysis is that the 4-second epoch starting ½ second after the auditory stimuli could be long enough that the classifier was based entirely on EMG noise related to the spoken response to the stimuli. While there is certainly some noise used in the classification, the mean length of the primary audio stimuli is 4.85 seconds (stdev = 0.996, min = 3.62, max = 7.19), suggesting that we are not classifying solely based on EMG noise related to speaking.

6 Conclusion

To begin developing aBCIs and related systems such as BCITs that function in noisy environments in which individuals are responsible for multiple concurrent tasks, we have demonstrated a basic ability to classify when a Soldier is listening to a relevant audio com, i.e. one that is addressed to them, and to which they later respond. It is clear that performance must be improved before using this classifier in an application. As such, we are exploring ways to improve and further our analysis through the use of multiple methods for extracting information from EEG data. For example, Independent Components Analysis (ICA) can remove eye [12] and other artifacts [13] from the EEG data, while connectivity measures such as Phase-Lag Index (PLI, [14]) can be insensitive to many movement artifacts [15]. Finally, we will need to evaluate the resulting performance in real-time in order to explore providing minor optimizations to crew station interfaces.

However, one remaining question is whether the classifier is learning from true brain data, or if it is primarily keying off of other physiological artifacts, such as EMG or EOG activity in the EEG recording. From the perspective of better understanding the cognitive processes associated with attending relevant audio stimuli such a question raises a clear, valid point. From the point of view of developing functional systems that operate robustly in complex environments, we would argue that, given the state of current technology, limiting research exploration to only explicitly demonstrated brain signals is neither pragmatic nor beneficial. It is not yet clear how much useful information is contained in the "noise" of the EEG data, and if the presence of this information improves, or at least does not hinder, the overall operation of an aBCI or similar system it may not be practical or even possible to completely remove such noise in real time.

In this paper, we described an experiment in a complex, high-noise, simulated environment, and we demonstrate that we are able to classify relevant audio coms with an intended response from irrelevant audio coms using EEG data collected during this experiment. In addition, we have described a planned analysis pipeline that should provide improved results over the performed preliminary analysis. By successfully processing complex, noisy data such as that described in this paper, we move closer towards being able to develop capabilities for detecting cognitive and affective states from EEG and other physiological data in real-world environments.

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